Image-Based Food Classification for Nutritional Information Estimation Using Deep Learning

Sahrial Ihsani Ishak[1)*], Sri Dianing Asri[2)], Bias Yulisa Geni[3)], Okma Arnilia[4)], Tri Widodo[5)], Diva Maulana Ilham[6)]
[1)2)3)6)]Fakultas Teknik dan Informatika, Universitas Dian Nusantara, Indonesia
[4]Fakultas Ilmu Tarbiyah dan Keguruan, Universitas Islam Negeri Siber Syekh Nurjati Cirebon, Indonesia,
[5]Fakultas Teknik dan Ilmu Komputer, Universitas Teknokrat Indonesia, Indonesia
[1)]sahrial.ihsani.ishak@dosen.undira.ac.id, [2)]sri.dianing.asri@undira.ac.id, [3)]bias.yulisa.geni@undira.ac.id, [4)]okmaarnilia@uinssc.ac.id, [5)]tri_widodo@teknokrat.ac.id, [6)]411221113@mahasiswa.undira.ac.id

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Abstract: This study aims to develop an image-based food classification application integrated with nutritional information retrieval using a deep learning approach. The proposed system is designed to recognize food types from images and provide nutritional information based on an Indonesian food nutrition database. The method involves collecting a dataset of 8,248 images representing 38 categories of Indonesian traditional foods, performing image preprocessing and data augmentation, and developing a Convolutional Neural Network (CNN) model based on the MobileNetV2 architecture through transfer learning. Model performance was evaluated using a 3-fold stratified cross-validation strategy and measured using accuracy, precision, recall, and F1-score metrics. Experimental results showed that the proposed model achieved average accuracy, precision, recall, and F1-score values of 98.85%, 98.88%, 98.85%, and 98.85%, respectively, demonstrating robust and consistent classification performance across the validation folds. The trained model was subsequently deployed into a mobile application using TensorFlow Lite to support real-time food classification and nutritional information presentation. The main contribution of this study is the development of an end-to-end mobile system that integrates deep learning-based food classification with an Indonesian food nutrition database, enabling users to obtain calorie, protein, fat, and carbohydrate information quickly and conveniently for dietary monitoring and health awareness.

Keywords: Food Classification; Deep Learning; MobileNetV2; Nutritional Information Retrieval; Mobile Application

INTRODUCTION

Nutrition problems are one of the main challenges in the field of public health, which due to unbalanced food consumption patterns can lead to various diseases such as obesity, diabetes, and cardiovascular diseases (World Health Organization, 2023). In Indonesia, nutrition problems are still a complex issue, characterized by the phenomenon of double burden, namely the coexistence between malnutrition and overnutrition in one population (Popkin et al., 2020; Hanandita & Tampubolon, 2015; Muharram et al., 2025). Monitoring food intake and nutritional content is very important as a preventive step in maintaining individual health (Diana, 2020; GBD Diet Collaborator, 2019; Rachmi et al., 2016).

However, conventional methods of calculating nutritional intake still have various limitations, as users generally have to record the food consumed manually and calculate their nutritional content using reference tables or text-input-based applications (Bailey, 2021; Eldridge et al., 2018; Shim et al., 2021). This approach tends to be time-consuming, less practical, and prone to human error, such as errors in identifying food types or estimating portions (Park et al., 2018; Teixeira et al., 2018; Höchsmann & Martin, 2020; Nohara & Koyama, 2025).

As technology develops, particularly in the field of artificial intelligence and image processing, there is an opportunity to overcome these limitations through an image-based automated approach, where deep learning, especially Convolutional Neural Network (CNN), has shown excellent performance in a wide range of image classification tasks, including object and food recognition (Liu et al., 2025; Ciocca et al., 2021). This technology can automatically recognize food types only from images taken using cameras, and has been implemented in

*Sahrial Ihsani Ishak

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various studies using CNN architectures such as AlexNet, VGGNet, ResNet, and MobileNet with high accuracy (Liu et al., 2021; Zhang et al., 2023; Udayana et al., 2020; Tan & Le, 2019). Some studies have also combined image processing with additional information such as portion sizes to estimate food calories (Liang et al., 2017; Nogay et al., 2025; Meyers et al., 2015).

However, most of these studies are still limited because they only focus on one aspect, both food classification and nutritional value estimation separately, and are still limited to a controlled environment or use a relatively small dataset (Lo et al., 2020; Surekha et al., 2025; Konstantakopoulos et al., 2023). In addition, the integration between food classification systems and real-time nutrition content databases has not been widely developed, so existing systems are not yet fully capable of providing practical solutions for use in daily life (Shetgaonkar et al., 2025).

Based on the literature review, a clear research gap remains in the development of practical systems that integrate image-based food classification with nutritional information retrieval within a single user-friendly mobile application (Konstantakopoulos et al., 2023; Surekha et al., 2025). While previous studies have primarily focused on food recognition or nutritional assessment as separate tasks, limited research has addressed their integration into an end-to-end system suitable for real-time use. Therefore, this study aims to develop an image-based food classification application using a deep learning approach and to integrate the classification results with a nutritional database to provide fast and practical nutritional information for dietary monitoring (Liu et al., 2025; Zhang et al., 2023; Shetgaonkar et al., 2025).

LITERATURE REVIEW

Digital Image Processing and Nutrition Problems

Nutrition issues are one of the important issues in public health that have a direct impact on the quality of life of individuals (World Health Organization, 2023; GBD Diet Collaborator, 2019). Imbalances in nutrient intake, both in the form of deficiencies and excesses, can trigger various diseases such as obesity, diabetes, and other metabolic disorders. In daily practice, monitoring food consumption is generally still carried out manually, such as recording the type of food and estimating its nutritional content. However, this approach has limitations because it relies on user subjectivity and often results in less accurate estimates (Bailey, 2021; Eldridge et al., 2018; Shim et al., 2021).

Along with the development of digital technology, various intelligent system-based approaches have begun to be developed to help the process of identifying food and estimating its nutritional content automatically (Konstantakopoulos et al., 2023). One widely used approach is the use of digital imagery as the primary source of information, where images of food taken through smartphone cameras can be processed to automatically recognize the type of food (Liu et al., 2025; Ciocca et al., 2021; Zhang et al., 2023).

Digital image processing is a technique used to extract information from images by utilizing visual characteristics such as color, texture, shape, and pattern. In the context of food, these characteristics become an important feature to distinguish one type of food from another (Liu et al., 2025). However, the image-based food identification process has various challenges, such as lighting variations, shooting angles, complex backgrounds, and visual similarities between food types (Liu et al., 2025). In addition, food is often served in mixed forms or has a non-uniform structure, making it difficult to segment and classify (Konstantakopoulos et al., 2023; Liang et al., 2017).

To overcome these challenges, a method is needed that is able to extract features automatically and robustly against data variations. Traditional methods in image processing have limitations in handling the complexity of food data, so machine learning-based approaches, especially deep learning, are more effective solutions (Liu et al., 2025).

Deep Learning with MobileNetV2 for Food Classification

The development of deep learning has brought significant changes in the field of image recognition, especially through the use of Convolutional Neural Network (CNN) which is capable of extracting features automatically without the need for manual feature engineering (Liu et al., 2025). CNN works by utilizing convolutional layers to detect local patterns in images, such as edges, textures, and shapes, which are then combined into more complex representations of features.

Various CNN architectures such as AlexNet, VGGNet, and ResNet have been developed to improve image classification performance (Zhang et al., 2023). However, such models generally have high computational complexity, making them less efficient to implement on mobile devices with limited resources (Konstantakopoulos et al., 2024).

As a solution, a lighter and more efficient CNN architecture was developed, one of which is MobileNetV2 (Sandler et al., 2018). This model is specifically designed for devices with computing limitations such as smartphones, while maintaining competitive performance. MobileNetV2 uses the concept of depthwise separable convolution to reduce the number of parameters and computational load, as well as inverted residual blocks and

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linear bottlenecks to improve the efficiency of feature representation. With these characteristics, MobileNetV2 is one of the right choices for mobile-based image classification applications (Udayana et al., 2020; Gulzar, 2023).

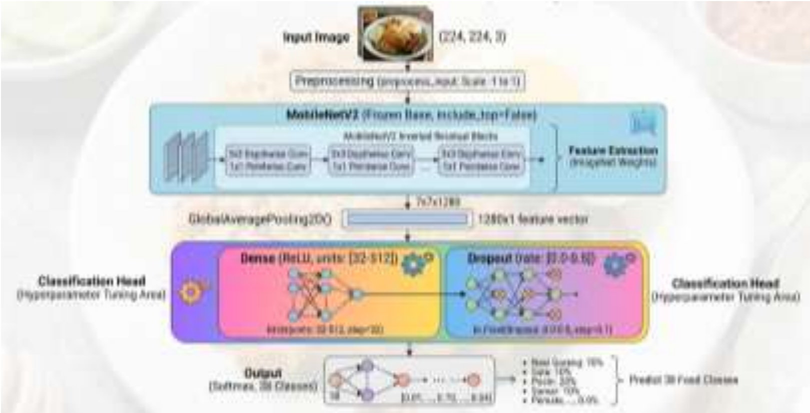

Fig. 1 Arsitektur MobileNetV2

Mobile Flutter and TensorFlow Lite Apps

The development of mobile applications for the detection of food nutritional content requires the integration of deep learning models and interactive user interfaces. In this study, Flutter is used as a cross-platform application development framework that allows the efficient integration of artificial intelligence-based systems. Flutter has advantages in terms of performance and interface design flexibility, so it is able to provide a responsive user experience (Aung et al., 2024).

In the implementation of the food detection system, mobile applications play a role in managing user interactions, such as taking pictures through cameras, processing inputs, and displaying the results of classification and nutritional content information. Image-based approaches have been shown to be effective in supporting the automated dietary assessment process (Liu et al., 2025; Konstantakopoulos et al., 2023).

To run deep learning models on mobile devices, TensorFlow Lite is used as a lightweight framework that supports the inference process efficiently on resource-constrained devices (Gulzar, 2023). The model implementation process involves a conversion stage to a lighter format as well as optimization using techniques such as quantization to reduce the model size and increase the inference speed without sacrificing accuracy significantly. After that, the model is integrated into the application so that it is able to infer in real-time the imagery that the user inputs (Udayana et al., 2020; Shetgaonkar et al., 2025).

METHOD

Fig 2 shows a research flow that uses a deep learning-based approach to develop a food type detection system and estimate the nutritional content of the image. The methods used include several main stages, namely system architecture design, dataset collection, data preprocessing, model development, nutritional content calculation, application implementation, and model performance evaluation.

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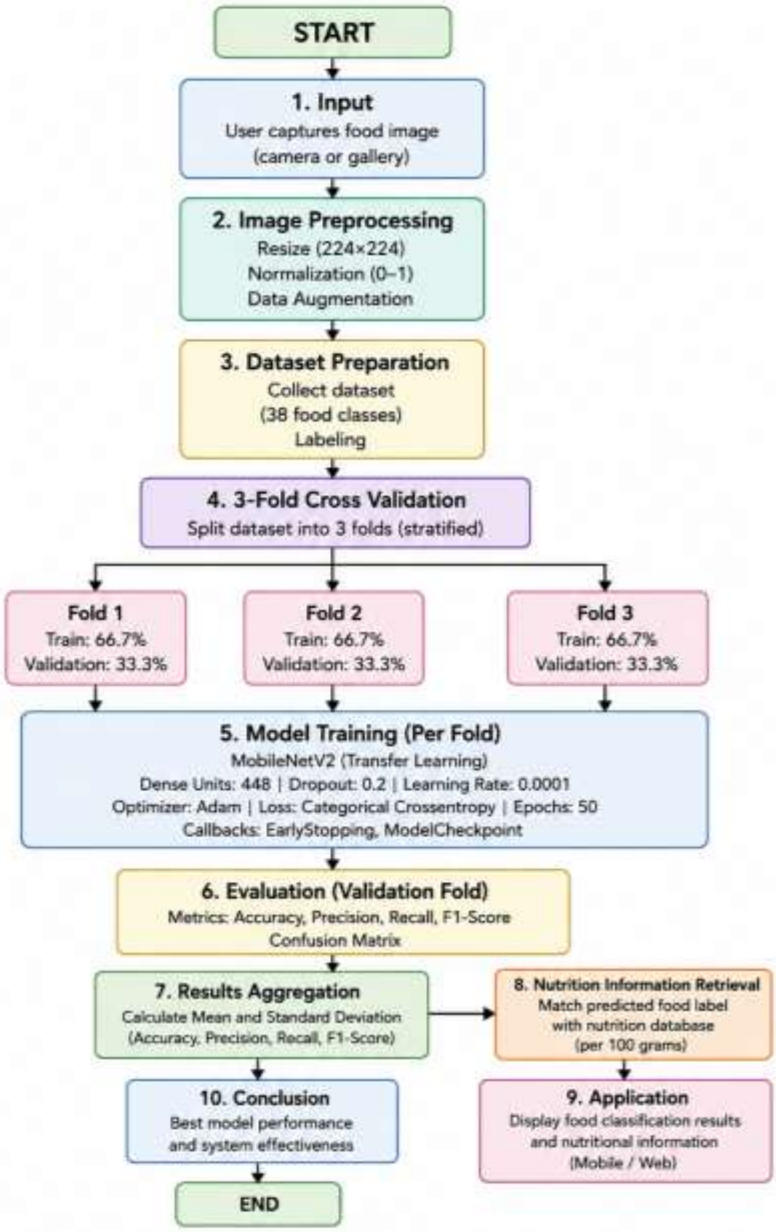

Fig. 2 Research flow

System Architecture

The proposed system architecture consists of three main components, namely inputs, processes, and outputs. At the input stage, the system receives the food images obtained through the device's camera or user gallery, which then goes directly through preprocessing stages such as resizing and normalization. This aims to ensure the uniformity of data formats before being processed by deep learning models (Mezgec & Seljak, 2017; Aslan et al., 2020).

Furthermore, the image is processed using a classification model based on the Convolutional Neural Network (CNN) to identify the type of food based on visual features, where the prediction results in the form of food labels are used in the process of estimating nutritional content through mapping with a nutrition database, so that the system produces output in the form of information on the type of food and its nutritional content such as calories, protein, fat, and carbohydrates that are automatically presented to the user (Kagaya et al., 2014; McAllister et al., 2018; Yunus et al., 2019; Liu et al., 2025; Zhang et al., 2023; Papathanail et al., 2023).

Datasets Used

The dataset used in this study consists of around 8,248 food images covering 38 categories of Indonesian food, obtained from a combination of public datasets and image scraping results (Udayana et al., 2020).

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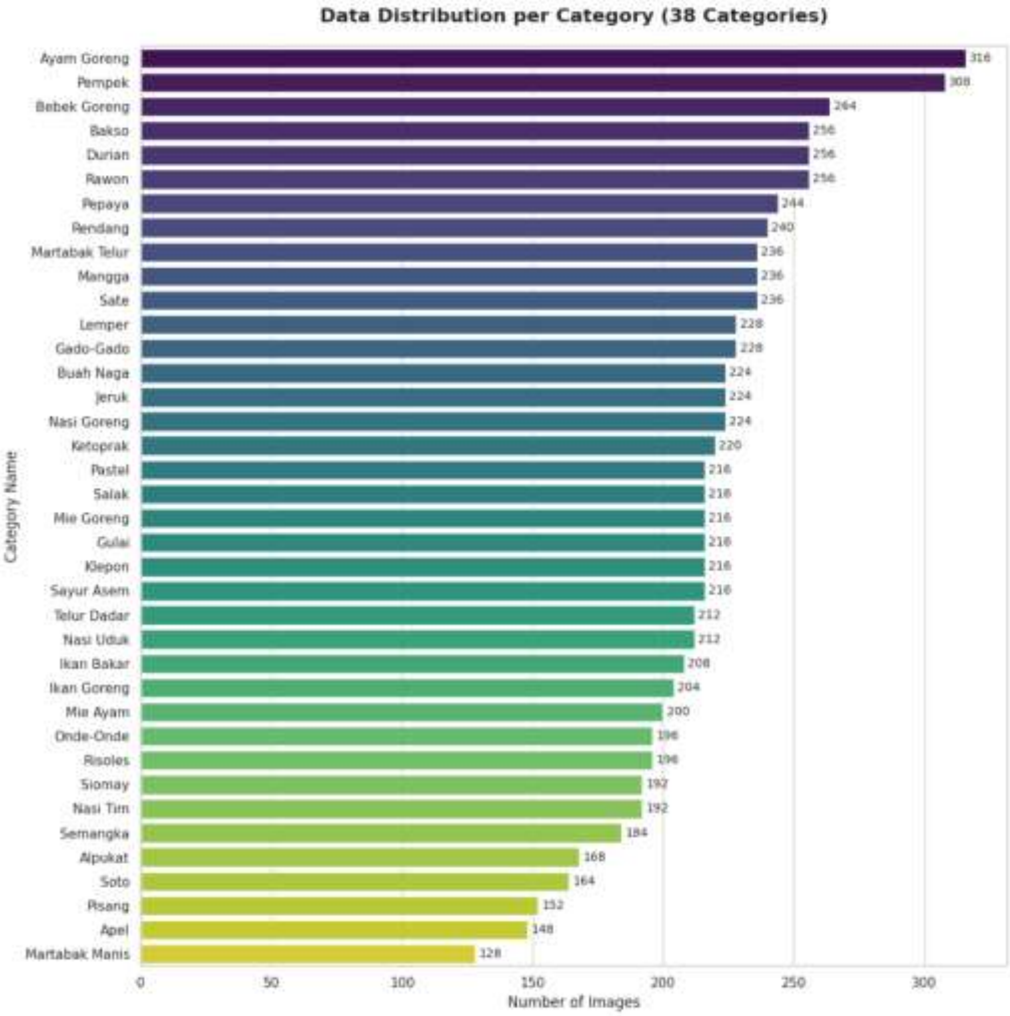

Fig. 3 Data Distribution per Category

To ensure robust model evaluation and reliable generalization performance, the dataset was assessed using a 3-fold stratified cross-validation approach. In this procedure, the dataset was divided into five mutually exclusive folds while preserving the class distribution across all food categories. For each iteration, four folds were used for training and one fold was used for testing, and the process was repeated five times so that each fold served as the testing set once. The final performance was obtained by averaging the evaluation results across all folds. In addition, data augmentation techniques, including rotation, flipping, zooming, and brightness adjustment, were applied only to the training data in each fold to increase data diversity and reduce the risk of overfitting (Singh & Susan, 2023; Mahgoub et al., 2023).

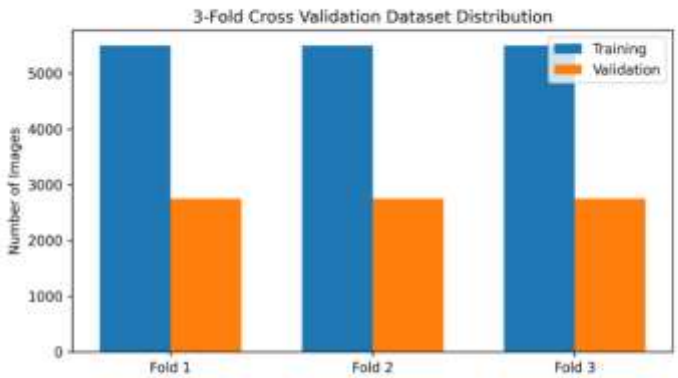

Fig. 4 Data Preparation for Modeling

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Modeling

The model used in this study is a Convolutional Neural Network (CNN) based on a transfer learning approach, which has demonstrated strong performance in image classification tasks (Liu et al., 2025). The MobileNetV2 architecture was selected due to its computational efficiency, lightweight design, and suitability for deployment on mobile devices with limited computational resources. MobileNetV2 employs depthwise separable convolutions and inverted residual blocks, enabling efficient feature extraction while maintaining competitive classification performance (Udayana et al., 2020; Singh & Susan, 2023).

The transfer learning approach utilizes a MobileNetV2 model pre-trained on the ImageNet dataset, where the convolutional layers act as feature extractors and the final classification layers are adapted to the 38 food categories used in this study. Model evaluation was conducted using 5-fold stratified cross-validation to ensure robust performance assessment and reliable generalization across different data partitions. The model was trained using the Adam optimizer with a learning rate of 0.0001 and the categorical cross-entropy loss function. Based on the best hyperparameter configuration, a dense layer consisting of 448 units and a dropout rate of 0.2 were employed. Training was performed for a maximum of 50 epochs, while an Early Stopping callback with a patience parameter was applied to prevent overfitting and retain the best-performing model during the training process (Mahgoub et al., 2023).

Automatic Nutrition Detection Mobile Application

The system is implemented in the form of a mobile application to allow users to detect food practically and in real-time through smartphone cameras. This approach is commonly used in image-based dietary assessment systems (Konstantakopoulos et al., 2023).

The trained model is then converted to the TensorFlow Lite format so that it can run efficiently on mobile devices. This process allows inferences to be made quickly without significantly sacrificing performance (Gulzar, 2023). The integration between image capture, classification model, and user interface allows the system to provide the analysis results directly to the user (Shetgaonkar et al., 2025; Udayana et al., 2020).

Indonesian Cuisine Nutrition Database per 100 grams

Table 1 presents the structure of the Nusantara Cuisine Nutrition Database which is used as a reference in the process of estimating nutrition after the food image is classified. The entire nutritional content is calculated in a standardized manner per 100 grams, including calories, protein, fat, and carbohydrates. The integration between the classification results and the database allows the system to automatically provide accurate and measurable nutritional information to the user (Liu et al., 2025).

Table 1
Sample Nutritional Value Database

No	Name	Calories	Proteins	Fat	Carbohydrate	Image
1	Avocado	85.0	0.9	6.5	7.7	URL
2	Apple	57.5	0.4	0.4	13.8	URL
3	Fried Chicken	298.0	34.2	16.8	0.1	URL
4	Meatballs	260.0	14.0	10.0	28.0	URL
5	Fried Rice	267.0	5.5	10.0	38.0	URL
…	…	…	…	…	…	...
38	Omelet	251.0	16.3	19.4	1.4	URL

Evaluate the Best Model

Model evaluation was carried out using test data that was not involved in the training process to measure generalization ability to new data. The evaluation metrics used include accuracy (Equation 1), precision (Equation 2), recall (Equation 3), and F1-score (Equation 4), which are standard in the evaluation of deep learning-based image classification models (Singh & Susan, 2023; Mahgoub et al., 2023). Accuracy measures the overall accuracy of a prediction, while precision and recall are used to evaluate false positive and false negative errors. The F1-score is used as a measure of the balance between precision and recall, especially on unbalanced datasets. In addition, a confusion matrix is used to analyze the distribution of misclassification in more depth.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

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Where TP (True Positive) is a condition when the model correctly predicts a positive class, TN (True Negative) when the model correctly predicts a negative class, FP (False Positive) when the model predicts positive when it is actually negative, and FN (False Negative) when the model predicts negative when it is actually positive.

RESULT

This chapter presents the results of experiments that have been carried out in the research comprehensively, including the model training process, performance evaluation, system implementation in the application, and analysis of the results obtained. The discussion not only focused on presenting numbers or performance metrics, but also interpreted the results by linking them to theories in the fields of deep learning, computer vision, and food informatics. With this approach, the results of the study are not only descriptive, but also provide a deeper understanding of how and why models work with certain performances. In addition, the advantages and limitations of the system were also discussed, as well as comparisons with previous research to affirm the contribution of this research in the development of image-based nutrition detection systems.

Model Training Results

Fig. 5. Training and Validation Learning Curves of the MobileNetV2 Model. The learning curves presented in Fig. 5 illustrate the progression of training and validation accuracy and loss during the model training process. The MobileNetV2 model was trained using the Adam optimizer and categorical cross-entropy loss function for a maximum of 50 epochs. As shown in the figure, both training and validation accuracy increased rapidly during the early epochs and gradually converged to values above 99%, while the corresponding loss values decreased substantially and stabilized near zero. The best validation performance was achieved at approximately epoch 36, where the model attained a validation accuracy of 99.33%. After this point, only minor fluctuations were observed in both accuracy and loss values, indicating that the model had reached a stable convergence state.

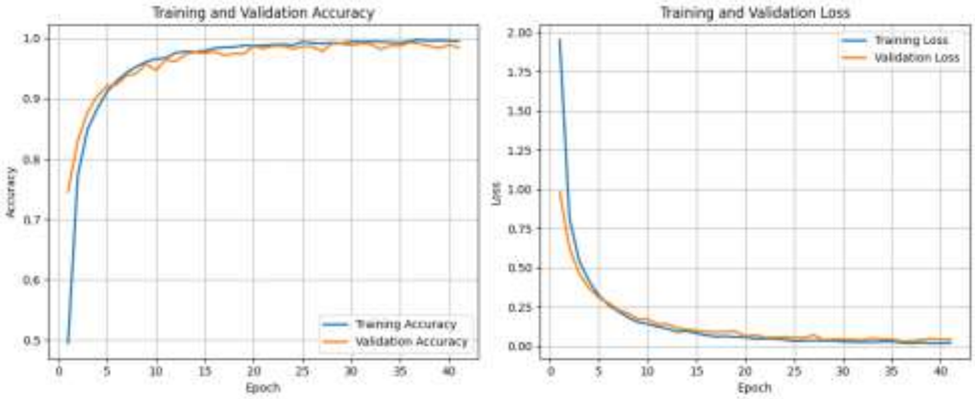

Fig. 5 Training Validation on Accuracy and Loss for Fold 3 (best fold)

The close correspondence between the training and validation curves suggests that the model learned meaningful and discriminative features from the food image dataset without exhibiting significant overfitting or underfitting. Furthermore, the consistently low validation loss and high validation accuracy across the later epochs indicate strong generalization capability on unseen validation data. These findings are consistent with the results obtained from the 3-fold cross-validation evaluation, confirming the robustness and effectiveness of the proposed MobileNetV2-based approach for Indonesian traditional food image classification and nutritional information retrieval.

Model Evaluation

Model evaluation was conducted using a 3-fold stratified cross-validation strategy to assess the generalization capability of the proposed MobileNetV2 model on unseen data. In each iteration, two folds were used for training and one fold was used for validation, ensuring that every sample was evaluated exactly once during the validation process. The model performance was measured using Accuracy, Precision, Recall, and F1-Score metrics. As presented in Table 2, the model achieved average Accuracy, Precision, Recall, and F1-Score values of 98.85%, 98.88%, 98.85%, and 98.85%, respectively. Furthermore, the low standard deviation values (0.0041–0.0043) indicate that the model produced stable and consistent performance across the three validation folds. These results demonstrate that the proposed MobileNetV2-based approach is effective in classifying Indonesian traditional food images and exhibits good generalization capability.

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Table 2 Model Evaluation Results

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	98.55	98.58	98.55	98.54
2	98.67	98.70	98.67	98.67
3	99.33	99.35	99.33	99.33
Std Dev	0.0042	0.0041	0.0042	0.0043

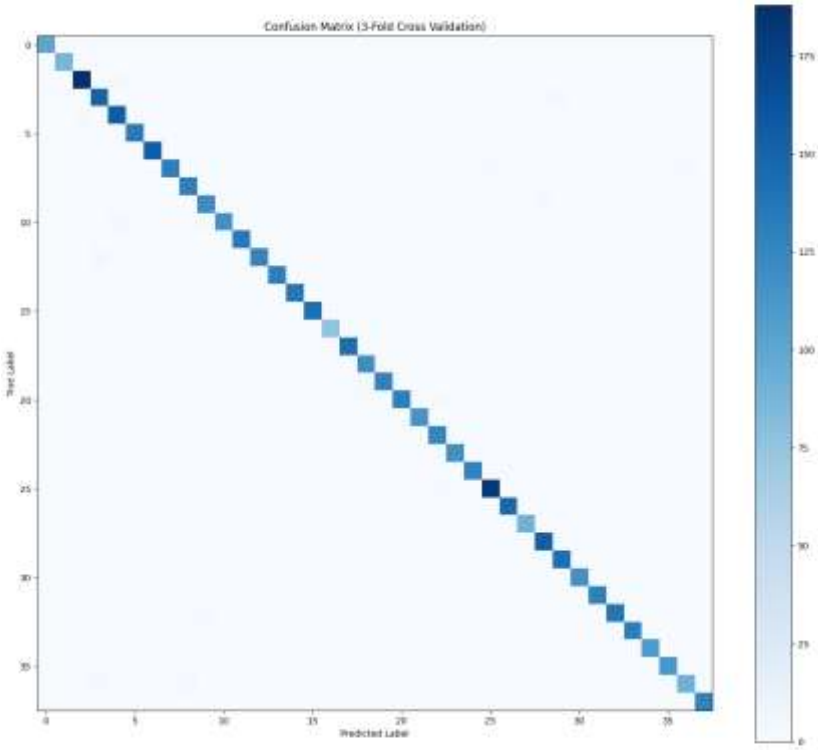

Fig. 6 Confusion Matrix

Fig. 6. Confusion Matrix of the MobileNetV2 Model Using 3-Fold Cross-Validation. The confusion matrix demonstrates the classification performance of the proposed MobileNetV2 model across 38 Indonesian traditional food classes. Most prediction results are concentrated along the main diagonal, indicating that the majority of samples were correctly classified into their respective classes. Only a small number of misclassifications appear outside the diagonal, suggesting minimal confusion between visually similar food categories. This result is consistent with the high evaluation metrics obtained during the 3-fold cross-validation process, where the model achieved average Accuracy, Precision, Recall, and F1-Score values above 98%. Overall, the confusion matrix confirms that the proposed model exhibits strong discriminative capability and robust generalization performance for multi-class food image classification.

Mobile Application Interface

Fig 7 shows the display of the mobile application "GiziKu: Scan Food" which is an image-based food detection system for estimating nutritional content. On the main screen, users can take pictures of food through the camera or choose from the gallery as system input. After the detection process, the application displays the classification results in the form of food types (e.g. "BANANA") along with their accuracy level of 100%. In addition, the system also presents detailed nutritional information such as calories, protein, fat, and carbohydrates in units per serving. The interface also provides additional features in the form of recommendations such as "Search Recipes (Cookpad)", "Cooking Videos (YouTube)", and "Complete Nutrition Info" to enrich user information.

Fig. 7 User Interface of the Mobile Application

DISCUSSIONS

The results of the 3-fold cross-validation demonstrate that the proposed MobileNetV2-based approach achieved consistently high classification performance across 38 categories of Indonesian traditional foods. The model obtained average Accuracy, Precision, Recall, and F1-Score values of 98.85%, 98.88%, 98.85%, and 98.85%, respectively, with low standard deviation values across the validation folds. These results indicate that the model was able to learn representative visual features from the dataset and maintain stable performance on unseen validation data. Furthermore, the learning curves showed a close correspondence between training and validation metrics, suggesting that the model converged successfully without significant overfitting or underfitting. The high classification performance confirms the suitability of transfer learning with MobileNetV2 for food image recognition tasks, particularly in resource-constrained environments such as mobile applications.

Despite the promising results, several misclassification cases were still observed. Analysis of the confusion matrix revealed that most errors occurred between food categories with similar visual characteristics, including comparable colors, textures, and presentation styles. For example, foods containing dominant red tones or similar gravy-based appearances were occasionally classified into incorrect categories. This observation suggests that the model primarily relied on global visual patterns and may have had difficulty distinguishing subtle local features under certain conditions. In addition, it is important to note that the proposed system does not directly estimate nutritional content from image pixels. Instead, nutritional information is retrieved from a predefined nutrition database after the food category has been identified. Therefore, the accuracy of nutritional information depends not only on the classification performance but also on the completeness and reliability of the nutritional database. Future studies may explore larger and more diverse datasets, fine-tuning strategies, attention mechanisms, and portion-size estimation techniques to improve both food recognition accuracy and nutritional assessment capabilities.

CONCLUSION

This study presented an image-based food classification and nutritional information retrieval system using a MobileNetV2 deep learning model and a nutrition database of Indonesian traditional foods. Using a 3-fold stratified cross-validation strategy, the proposed model achieved average Accuracy, Precision, Recall, and F1-Score values of 98.85%, 98.88%, 98.85%, and 98.85%, respectively, demonstrating stable performance and good generalization capability across different validation folds. The results indicate that transfer learning with MobileNetV2 is effective for recognizing Indonesian traditional food images and can be deployed efficiently in mobile-based applications.

The main contribution of this research lies in the development of an end-to-end system that integrates food image classification with nutritional information retrieval. After a food image is classified, the corresponding nutritional information is automatically obtained from a nutrition database, enabling users to access calorie, protein, fat, and carbohydrate information in a fast and practical manner. Although the system does not directly estimate nutritional content from image data, the proposed approach provides a practical solution for supporting dietary monitoring and nutrition awareness. Future work may focus on portion-size estimation, broader food categories, and direct nutrient prediction methods to further enhance the system's applicability in real-world nutritional assessment.

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*Sahrial Ihsani Ishak